



# **NAVAL POSTGRADUATE SCHOOL**

**MONTEREY, CALIFORNIA**

## **THESIS**

**AERIAL LOGISTICS MANAGEMENT FOR CARRIER  
ONBOARD DELIVERY**

by

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September 2016

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**AERIAL LOGISTICS MANAGEMENT FOR CARRIER ONBOARD DELIVERY**

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## **ABSTRACT**

Carrier onboard delivery (COD) is the use of aircraft to transport people and cargo from a forward logistics site (FLS) to a carrier strike group (CSG). The goal of this thesis is to study how the real-time cargo tracking capability can reduce the delay of high-priority cargo while increasing that of low-priority cargo. To do so, we analyze data from COD operations between 2010 and 2015 to develop a simulation model, and use those data to infer model parameters. Our simulation results indicate that, with two C-2A aircraft currently used by the Navy, real-time cargo tracking can reduce the delay of high-priority cargo by more than 50%, while increasing that of low-priority cargo by about 25%. The Navy plans to replace C-2A with a variant of V-22 Osprey for COD operations in the near future, and is conducting cargo space studies to facilitate this transition. By testing a few different model parameters based on studies available for V-22, our simulation results indicate a similar observation of delay tradeoff between high-priority cargo and low-priority cargo, although the tradeoff is less pronounced, mainly because three V-22 will be stationed at the FLS.

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## List of Acronyms and Abbreviations

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<b>CNA</b>	Center for Naval Analyses
<b>COD</b>	Carrier Onboard Delivery
<b>CSG</b>	Carrier Strike Group
<b>DV</b>	Distinguished Visitor
<b>FLS</b>	Forward Logistics Site
<b>NAS</b>	Naval Air Station
<b>OBBI</b>	Bahrain International Airport
<b>RFT</b>	Ready for Tasking
<b>SLEP</b>	Service Life Extension Program
<b>USMC</b>	United States Marine Corps
<b>USN</b>	United States Navy
<b>USSOCOM</b>	United States Special Operations Command

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## Executive Summary

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Carrier onboard delivery (COD) is the use of aircraft to transport people and cargo from a forward logistics site (FLS) to a carrier strike group (CSG). Currently, the U.S. Navy uses the C-2A(R) Greyhound to support the COD mission, but plans to replace it with CMV-22B Osprey in the near future. Since the Navy does not track all cargo items in real time, often cargo items with higher priority are unnecessarily delayed, while those with lower priority are shipped first. This thesis aims to study how a real-time cargo tracking system can reduce the delay of cargo of higher priority.

The Fleet Logistics Support Squadron 30 (VRC-30) provides data on COD operations between 2010 and 2015. The data set contains the COD sorties, the number of passengers transported, and the amount of cargo delivered. We work with VRC-30 to develop a simulation model for the COD operations, and use the data set to infer model parameters. Our simulation model is flexible to account for different operational scenarios and different aircraft types. By running the simulation model, we can estimate the delays of passengers and cargo when the FLS does not have real-time cargo tracking capability, as well as the delays when the FLS has real-time cargo tracking capability.

For an FLS with two standard C-2A Greyhound, our simulation results indicate that a cargo tracking system can reduce the delay of high-priority cargo by more than 50%, while increasing the delay of low-priority cargo by 25%. When the payload on C-2A drops, either when the CSG sits at a farther distance or when the temperature rises, this tradeoff is even more pronounced. It is more difficult to run our simulation model for an FLS with CMV-22B Osprey, since there are ongoing studies on its cargo space configuration. We use the numbers in a cargo study carried out by Naval Air Station Patuxent River in November 2014, and test a few different numbers in the same range. In those simulation experiments, our results indicate that a cargo-tracking system can reduce the delay of high-priority cargo by 17–35%, while increasing the delay of low-priority cargo by 8–17%.

Our simulation results depend heavily on model parameters, which can be fine-tuned and adjusted if further studies are available. Since there is no data on the volume and frequency of cargo and passengers arriving at the FLS, we make a few assumptions in our model

via educated guess. We do take into account the fact that aircraft go through breakdown and repair cycles, and assume different aircraft act independently through their individual cycles. This assumption may not hold in practice, if the parts of a broken aircraft can be used to repair another aircraft of the same type, in which case the breakdown of one aircraft actually makes the others more likely to remain operational. Another interesting research question is how cargo tracking can help alleviate the added delay of high-priority cargo when a surge of demand arrives at the FLS. The answers to these questions require further research.

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# CHAPTER 1:

## Introduction

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Carrier onboard delivery (COD) is the transport of high priority cargo, mail, and passengers between carriers and shore bases. COD operations are accomplished with airplanes with the ability to land onboard aircraft carriers. These airplanes fly from forward logistics sites (FLS) to the carrier to supply items critical to the entire carrier strike group (CSG), as well as the carrier itself.

The Navy currently uses C-2A Greyhound aircraft to support the COD operations [1], but lacks a comprehensive method of tracking and prioritizing cargo shipped to the CSG. Consequently, limited aircraft shipping space/weight is often allocated to low priority items while high priority items are left behind. As the Navy will soon replace the C-2A with CMV-22B—a Navy variant of the V-22 Osprey—to support the COD mission, the goal of this thesis is to assess the value of near real-time end-to-end tracking of individual cargo items for both C-2A and CMV-22B in the COD mission [2].

### 1.1 Carrier Onboard Delivery

Critical logistics support to Carrier Strike Groups has been provided by multiple aircraft types since the first COD flight was made in June 1958, from Naval Air Station (NAS) North Island to the USS *Yorktown* (CV-10). This flight was accomplished by the Grumman C-1A Trader aircraft.

The C-2A Greyhound began to replace the C-1A Trader for COD operations with the first prototype flight in 1964, and has been providing critical logistics support to Carrier Strike Groups for five decades [3]. The C-2A Greyhound has the ability to transport large priority cargo items, such as jet engines, from the shore to a ship in a matter of hours. Faster loading and unloading is provided by the C-2A Greyhound's aft cargo ramp/door [1].

To extend their operational life, the original C-2As were overhauled in 1973. In 1984, the Navy contracted for 39 new C-2A aircraft. Compared to the original C-2A, these reprocurd C-2A, or C-2A(R), have improved airframes and avionic systems. By 1987, all the original

airframes were phased out, and the last of the reprocured models was delivered in 1990. Currently, the C-2A Greyhound is undergoing a Service Life Extension Program (SLEP) to increase its operating service life [1].

The Navy is planning to replace the C-2A with V-22 Osprey for the COD mission in the coming years. The V-22 is a dramatically different airplane, as seen in Figure 1.1. The V-22 Osprey was developed for many different applications, including United States Marine Corps (USMC), United States Navy (USN), and United States Special Operations Command (USSOCOM) combat missions. It is a tiltrotor aircraft jointly built by Bell Helicopter Textron and Boeing Defense and Space Group, Helicopter division [4], [5]. The tiltrotor gives the aircraft the ability to take off and land vertically like a helicopter, and once airborne, convert to a turboprop airplane like the C-2 Greyhound, by rotating the wings. The V-22 was developed from the technologies of the experimental XV-15 tiltrotor design from the 1980s. In 1996, during Operational Tests and Evaluations, “the V-22 demonstrated several capabilities not achievable by current medium-lift helicopters” [5]. From 2018 to 2020, the Navy plans to buy eight V-22 Osprey per year for COD operations [6]. The V-22 variant that will be used for COD operations will be called the CMV-22B [7].

## 1.2 Cargo Tracking Capability

Modern consumer shipping service providers, such as FedEx and UPS, provide end users with shipping time estimates and regularly updated status information on any package’s location. Consumers may also pay for expedited shipping for items they need urgently. These

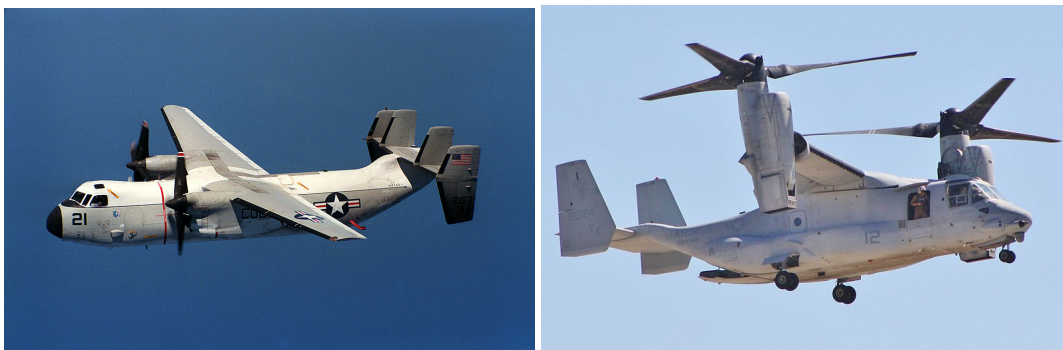


Figure 1.1. C-2 Greyhound and V-22 Osprey

US Defense Visual Information Center *Wikipedia* [Online] Available: [https://commons.wikimedia.org/wiki/File:C-2A\\_DN-SC-89-09037.JPEG](https://commons.wikimedia.org/wiki/File:C-2A_DN-SC-89-09037.JPEG) Accessed Sep. 12, 2016

Wikimedia Commons *Wikipedia* [Online] Available: [https://commons.wikimedia.org/wiki/File:MV-22\\_mcas\\_Miramar\\_2014.JPG](https://commons.wikimedia.org/wiki/File:MV-22_mcas_Miramar_2014.JPG) Accessed: Sep. 12, 2016

companies have a much larger and diverse network of transportation with regularly scheduled shipping routes by ground and air. With multiple origins and multiple destinations, there are multiple routes any package can take. A delivery company would make delivery decisions to minimize costs, while satisfying the delivery constraints promised to the customer. Commercial shipping companies typically use large airplanes, such as the Boeing 777, to ship cargo.

In contrast, COD operations represent the ‘last leg of the journey’ and have only one point of origin and one destination. As a military operation, the timely delivery of higher priority items would be more important than cost and fuel savings. The requirement for the COD to land onboard an aircraft carrier places further engineering constraints on the airplane. Figure 1.2 contrasts these two situations [8].

The flexibility of the COD is touted as one of its best assets, as the ability to configure and reconfigure the aircraft to meet different cargo and passenger loads in a relatively short time period is extremely beneficial to a CSG. In 2016, the Navy does not have a real-time end-to-end tracking system for the cargo, and the loading and unloading of the plane is done manually. Sometimes lower priority items are loaded onto the plane and then have to be unloaded to make room for higher priority items. The handling of heavy cargo in the low height environment has caused back issues for some crew and an ergonomic study found the environment to be unhealthy for exoskeletons. Recommendations have been made to improve the loading methods and equipment, such as pallets with wheels, to address these issues. An improved tracking capability of cargo could also help address these issues [2].



Figure 1.2. FedEx Boeing 777 (left) and V-22 configured to fly four people (right) Source: [8]

### 1.3 Two Aircraft Platforms

The capabilities of C-2 Greyhound [9] and V-22 Osprey [10] are summarized in Table 1.1. The C-2 Greyhound has larger cargo space, slightly faster cruise speed, and a longer range. The V-22 has a larger maximum payload of 20,000 pounds than the C-2 maximum payload of 10,000 pounds for ground operations and 8,600 pounds for carrier operations [11], [12]. However, V-22 Osprey can take off and land vertically, and is more versatile to support a variety of missions. Variants of V-22 are also used by the United States Marine Corps and United States Air Force [2], [4], [13].

The C-2 Greyhound has been used for COD operations since the 1960's, and the configuration of its use for COD flights is well documented. Each FLS typically has two C-2 Greyhound planes stationed to carry out COD operations. To prepare V-22 for the COD operations in the near future, NAS Patuxent River conducted cargo loading evaluations and demonstrations in 2014, and provided several possible configurations of the V-22 for COD operations. In the coming months, the Center for Naval Analysis (CNA) will release reports to revise the cargo loads from these previous studies [14]. The plan is to station three V-22 Ospreys at a FLS [2], [13].

Table 1.1. Comparison between C-2 and V-22 Platforms. Adapted from [4], [9].

	C-2 Greyhound	V-22 Osprey
Crew	2 pilots / 2 aircrew	2 pilots / 2 aircrew
Max Passengers	26 passengers	24 troops(seated), 32 (floor loaded)
Max Payload	10,000 lb	20,000 lb
Cargo Space	467 ft <sup>3</sup>	377 ft <sup>3</sup> (based on cage study)
Max Speed	343 knots	275 knots
Cruise Speed	251 knots	241 knots
Range	1300 nm	879 nm
Service Ceiling	33500 ft	25000 ft

### 1.4 Literature Review

The methods used to develop this thesis includes statistics, stochastic modeling, and simulation. The techniques used include estimation, Poisson process, discrete-event simulation,



and variance reduction. Interested readers can review Wackerly et al. [15], Papoulis [16], Ross [17], and Law and Kelton [18] for these technical topics. The data of past COD operations are provided by VRC-30, and processed via a statistical computing package, R [19]. The simulation model is implemented in Python [20] via a discrete-event simulation package SimPy [21].

## **1.5 Thesis Outline**

In Chapter 2, we explore data from C-2 Greyhound operations between 2010 and 2015. This data analysis provides critical parameters for use in our model. In Chapter 3, we develop a mathematical model for COD operations with help from VRC-30, a United States Navy Fleet Logistics Support squadron based at Naval Air Station North Island in San Diego. In Chapter 4, we present simulation results of the COD operations to learn how a real-time cargo tracking capability could reduce the delay of high priority cargo in a few operational scenarios. In Chapter 5, we conclude this thesis and offer a few recommendations and directions for future work.

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## CHAPTER 2:

### Data Analysis

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We use historical data to obtain reasonable parameters for the simulation of COD flight operations. VRC-30 provided data of COD operations between 2010 and 2015 [2]. The data covered five C-2 Greyhound detachments, serving nine carriers, from 96 different locations from the Pacific to the Middle East. Table 2.1 summarizes the FLS with more than 100 departing flights. Among these locations, the operations from Bahrain International Airport (OBBI) saw the heaviest traffic with 1046 departing sorties between 25 May 2010 and 3 June 2015, while the second is Kadena Air Base (RODN), in Japan, with 332 departing sorties between 12 July 2010 and 25 May 2015.

In this thesis, we use the data on the traffic from Bahrain to infer a plausible scenario for the COD operational environment. We then conduct a simulation study for that operational environment to assess how tracking technology affects the delay of the items shipped to the CSG from the FLS. The statistical computing language R is used to conduct data analysis [19].

Table 2.1. Forward logistic sites with over 100 departing flights in data set.

Forward Logistic Site	Airport Code	# Departing Flights
Bahrain Int Airport	OBBI	1046
Kadena Air Base	RODN	332
North Island Naval Air Station	KNZY	250
Naval Air Facility Atsugi	RJTA	229
Andersen Air Force Base (Guam)	PGUA	198
Hickam Field Airport (Honolulu)	PHIK	184
Al Udeid Air Base	OTBH	129
Clark International Airport	RPLC	125

## 2.1 Ready for Tasking

Ready for Tasking (RFT) is the long-run average of the number of planes available at the FLS. Based on conversations with VRC-30, the C-2 Greyhound averages at 1.5 planes ready for tasking during COD operations. In FLS supporting contingency operations, such as one located at the Bahrain International Airport, we observed at most two unique airframes at any given time. Figure 2.1 shows two unique airframes operating between OBBI and CV72 between October 2010 and February 2011, and then two different airframes operating between January 2012 and July 2012. In homeported environments, such as an FLS in San Diego, we observed many more airframes available to a carrier, as shown in Figure 2.2. These airframes supported not only the delivery of cargo and passengers, but also the testing and qualification of equipment and personnel. We will model the environment that is deployed and supporting contingency operations, with only two airframes available.

## 2.2 Flight Times

The flight time to travel from FLS to CSG and to return is modeled by a random variable. Figure 2.3 shows all the flight times from OBBI to a carrier. The shape is bimodal, with a sharp cutoff at 100 minutes. This is explained by the carrier operating at two different locations between 19 October 2010 and 10 July 2012. For simulation, a choice can be made as to whether the carrier is far away or close by the FLS. We use the triangular distribution to model the flight time, with the shorter flights having parameters (30, 65, 90) and the longer flights having parameters (100, 150, 200). A longer flight requires more fuel, and the aircraft may have a smaller payload due to weight restriction.

## 2.3 Time on a Carrier

By tracking individual aircraft, it is possible to infer the amount of time a C-2A Greyhound spends onboard the carrier. The plane typically spends less than two hours onboard the carrier, before departing again. But the distribution also has huge tails, indicating the plane spends up to several days onboard the carrier before departing. This extended delay can be attributed to minor mechanical or electrical problems that need to be fixed or tuned, or to other reasons. Figure 2.4 gives the distribution of a typical plane from the data by cutting off the long tail that exceeds 120 minutes. The delay with less than 120 minutes accounts for about two thirds of the cases, while the delay with more than 120 minutes accounts for

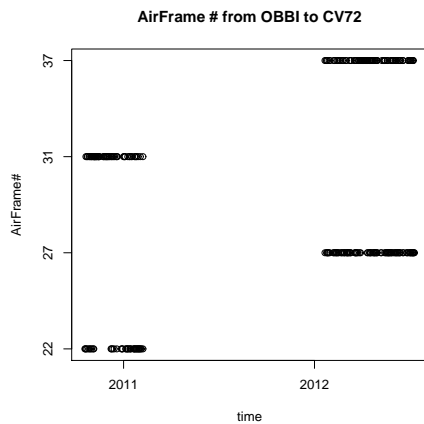


Figure 2.1. COD activities in Bahrain

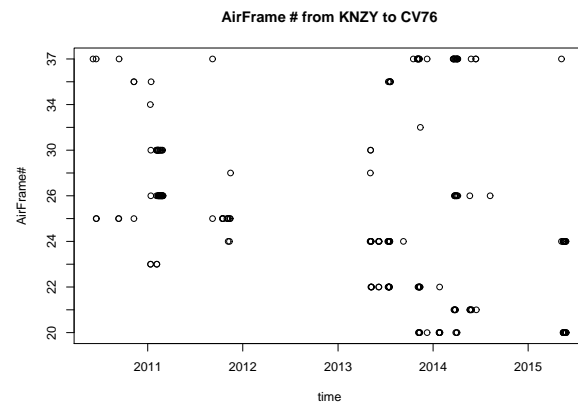


Figure 2.2. COD activities in San Diego

about one third of the cases, which typically extends to several days. The extended delay over 120 minutes will be modeled by repair time.

## 2.4 Cargo

Cargo shipped from the FLS to the CSG consists of a variety of things, including supplies, mail, food, replacement parts, luggage of the passengers, among others. The data provided by VRC-30 reports only the volume of each shipment, but not cargo types. The summary of data is presented in Table 2.2. As seen in Table 2.2, on average, each flight from OBBI to a carrier delivered 408 ft<sup>3</sup> of cargo, and each flight returning to OBBI delivered 254 ft<sup>3</sup> of cargo.

## 2.5 Passengers

The COD mission includes ferrying passengers between the FLS and the CSG. Some passengers are designated as ‘Distinguished Visitors,’ while the others are not. Each passenger typically brings along a personal belonging, which takes up cargo space. Among all FLS locations, on average, each flight carried 10.6 passengers, including an average of 1.5 Distinguished Visitors. For OBBI, on average, each flight carried 9.3 passengers, including an average of 0.86 Distinguished Visitors.

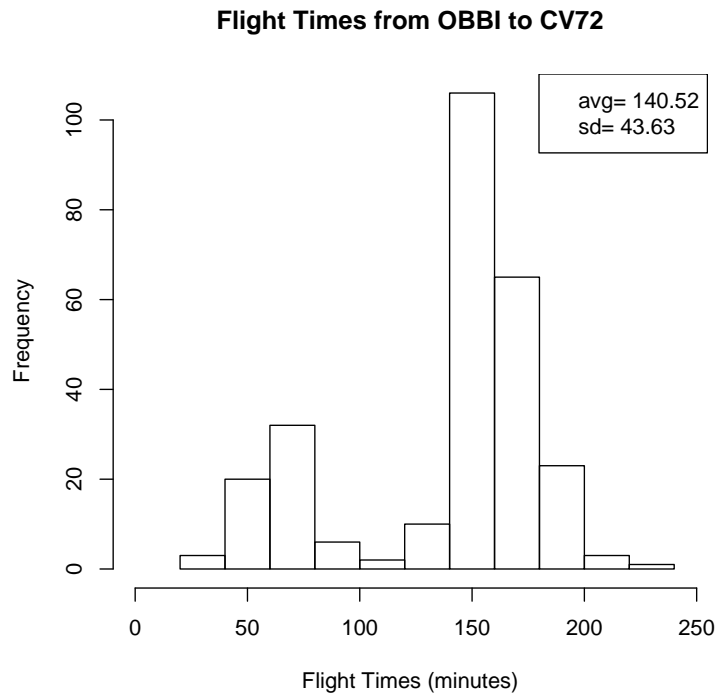


Figure 2.3. Distribution of Flight Times from OBBI to CVN72.

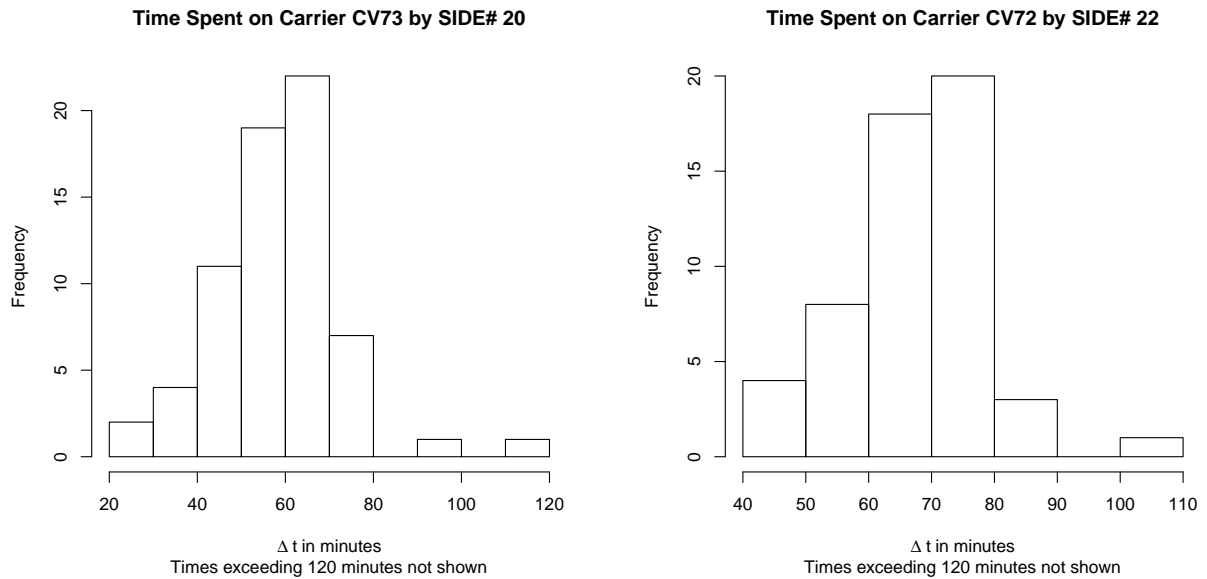


Figure 2.4. Distribution of Time Spent on a Carrier, if time is less than 120 minutes.

Table 2.2. Cargo and passengers transported between OBBI and a carrier

Direction	Time Period	Total				Average per Flight		
		Flight	Passengers	Cargo (ft <sup>3</sup> )	DV	Passengers	Cargo (ft <sup>3</sup> )	DV
Carrier to OBBI	Oct 2010 to Feb 2011	100	895	23397	121	9.0	234.0	1.2
	Sep 2011 to Jan 2012	90	964	19723	54	10.7	219.1	0.6
	Jan 2012 to Jul 2012	167	1441	47806	162	8.6	286.3	1.0
	Oct 2012 to Mar 2013	134	1220	33927	135	9.1	253.2	1.0
	Overall	491	4520	124853	472	9.2	254.3	1.0
OBBI to Carrier	Oct 2010 to Feb 2011	99	924	42125	105	9.3	425.5	1.1
	Sep 2011 to Jan 2012	106	1032	41677	72	9.7	393.2	0.7
	Jan 2012 to Jul 2012	172	1408	63587	143	8.2	369.7	0.8
	Oct 2012 to Mar 2013	146	1479	66188	132	10.1	453.3	0.9
	Overall	523	4843	213577	452	9.3	408.4	0.9

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## CHAPTER 3:

### A Simulation Model

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Based on data analysis presented in Chapter 2, we develop a simulation model for the carrier onboard delivery (COD) operations. A forward logistics site (FLS) carries out COD operations to support a carrier strike group (CSG). A FLS typically has 2 to 3 aircraft on base, but each aircraft may not always be available, as aircraft need to go through maintenance and repair at times. An aircraft can be configured in several different ways to transport both cargo and passengers.

Cargo that needs to be airlifted to the CSG arrive at the FLS over time (via convoys, postal service, UPS, etc.). Cargo packages vary in size and weight, but we will use the size as the single parameter—measured in cubic feet—since most of the time the limiting factor is the available cubic volume rather than cargo weight [2]. There are two types of cargo. The first cargo type consists of small replacement parts, supplies, mail, etc., whose volume will be treated as a continuous variable, so we can choose to load any amount. The second cargo type consists of large replacement parts, such as F-18 engines. A large replacement part needs to be loaded as a whole and takes up the entire cargo space. Furthermore, each cargo piece can be categorized into priority levels 1 to 4, with priority 1 being the highest.

Passengers who need to be airlifted to the CSG arrive at the FLS in groups. All the passengers in the same group need to be transported in the same flight from the FLS to the CSG. Each group consists of a number of passengers, which typically ranges from 1 to 5. Some passengers are distinguished visitors, who have priority 1; the other passengers have priority 2.

Although the aircraft also transports cargo and passengers from the CSG to the FLS, we do not model this traffic explicitly for two reasons. First, the delay of cargo on return trips is of secondary importance, so a simple policy that always gives priority to passengers would be effective. Second, as seen in Chapter 2, the amount of cargo on return trips is smaller than that on the forward trip (since some cargo such as food are consumed at the CSG), so it is not the bottleneck and does not adversely affect the system performance.

Below we make several quantitative assumptions about aircraft, cargo, and passengers. The model parameters are chosen to fit the data observed from the traffic between OBBI and CV72, as described in Chapter 2, so that they represent a real-world scenario. These model parameters can be changed to study different scenarios.

### 3.1 Cargo

There are two types of cargo that need to be transported from the CSG to the FLS. The first type includes small parts, supply, mail, etc., and is modeled by a continuous variable. Cargo of this type arrives at the FLS with an average of 5 shipments per day, and the times of arrival are modeled by a Poisson process. The cargo size in each shipment has expected value 50 cubic feet and standard deviation 10 cubic feet. We use the gamma distribution to model the amount of cargo that comes in each shipment. This distribution can have a bell shaped curve and is supported by the non-negative real numbers, so that the event of a very large shipment is possible. A shape parameter of  $k = 25$  and a scale of  $\theta = 2$  gives a distribution with the desired expected value and variance.

Let  $p_i$  denote the long-run fraction of cargo that are priority  $i$ , for  $i = 1, 2, 3, 4$ . We assume

$$p_1 = 0.05, \quad p_2 = 0.1, \quad p_3 = 0.2, \quad p_4 = 0.65.$$

Specifically, if the cargo size of  $x$  cubic feet arrives at the FLS, then we assume that  $x \cdot p_i$  of which has priority  $i$ , for  $i = 1, 2, 3, 4$ .

The second type of cargo are large replacement parts, such as F-18 engines. These large and important cargo arrive infrequently, and we model their arrivals as a Poisson process with rate 0.35 per day. Each cargo piece of this type has to be transported as a whole, and it takes the entire cargo space. In other words, a sortie that transports a large replacement part cannot transport any passenger or additional cargo. This constraint applies to both C-2 Greyhound and V-22 Osprey. For accounting purpose, we assume that the average size of this type of cargo piece is 250 cubic feet.

With these assumptions, the average daily amount of cargo that needs to be transported

from the FLS to the CSG is

$$50 \times 5 + 250 \times 0.35 = 337.5 \quad (3.1)$$

cubic feet per day.

### 3.2 Passengers

Passengers come to the FLS in groups. We model these groups arriving to the FLS as a Poisson process, with rate 7.5 per day. The number of passengers in each group ranges between 1 and 5 passengers, with respective probabilities

$$0.7, \quad 0.2, \quad 0.05, \quad 0.03, \quad 0.02.$$

We assume that the numbers of passengers in different groups are independent. Passengers in the same group have to be transported in the same flight. A group has priority 1 if it includes at least one distinguished visitor, otherwise it has priority 2. We assume that each group has a probability 0.15 of having priority 1, regardless of its size.

Each passenger has personal luggage that also takes up cargo space. As seen in Table 3.2, the cargo space of V-22 can be configured to carry a maximum of 17 passengers along with 128 cubic feet of cargo. If the entire cargo space is reserved for passenger luggage, then each passenger is afforded  $128/17 \approx 7.5$  cubic feet of luggage space. This number was confirmed as reasonable by VRC-30 email communication. In our model, we assume that each passenger brings personal luggage that takes up 7.5 cubic feet of cargo space. For instance, transporting 3 passengers takes 3 seats and  $7.5 \times 3 = 22.5$  cubic feet of cargo space.

With these assumptions, the average number of passengers that need to be transported from the FLS to the CSG per day is

$$7.5 \times (0.7 \times 1 + 0.2 \times 2 + 0.05 \times 3 + 0.03 \times 4 + 0.02 \times 5) = 11.025.$$

These passengers will also bring

$$11.025 \times 7.5 = 82.69$$

cubic feet of personal luggage per day. Together with cargo in Equation (3.1), the average amount of cargo that needs to be transported from the FLS to the CSG is thus

$$337.5 + 82.69 = 420.19$$

cubic feet per day. These numbers are consistent with data observed from the traffic between OBBI and the carriers from October 2010 to July 2012.

### **3.3 Aircraft**

Currently, a typical FLS is equipped with two C-2A Greyhound aircraft to support the COD mission. In the coming years, the Navy will switch from C-2A Greyhound to V-22 Osprey to support the COD mission. Each FLS will be equipped with three V-22 aircraft. Aircrafts can be configured differently, depending on the situation, to carry different amount of cargo and number of passengers.

#### **3.3.1 C-2 Greyhound**

C-2 has nine sections of cargo space. The first two sections (nearest the cockpit) are always configured for cargo, while the aft section is always configured to be a row of four seats for two aircrew men [2]. Each of the middle six sections can be used to hold cargo or configured to a row of four seats. The feasible configurations are shown in Table 3.1 and a diagram of the nine cargo sections is given in Figure 3.1.

Recall that in our model, each passenger's luggage takes 7.5 cubic feet of cargo space. Therefore, the actual space available for cargo is reduced by the same amount. For instance, if we configure the C-2 cargo space into 4 rows of seats and 5 sections of cargo, and transport 14 passengers, then the available cargo space reduces to only

$$259 - 7.5 \times 14 = 154$$

Table 3.1. Feasible C-2 cargo space configurations.

Configuration	Cargo (cubic feet)	Passengers	Equivalent
7 rows of seats and 2 sections of cargo	103	26	441
6 rows of seats and 3 sections of cargo	155	22	441
5 rows of seats and 4 sections of cargo	207	18	441
4 rows of seats and 5 sections of cargo	259	14	441
3 rows of seats and 6 sections of cargo	311	10	441
2 rows of seats and 7 sections of cargo	363	6	441
1 row of seats and 8 sections of cargo	415	2	441

cubic feet. If we use 6 rows of seats and 3 sections of cargo, then we can seat at most 20 passengers and transport their luggage

$$7.5 \times 20 = 150$$

cubic feet, since the cargo space 155 cubic feet is not enough to carry all the luggage if we seat 21 or 22 passengers.

Once we decide to fly a sortie, we need to load cargo and let the passengers board the aircraft. We assume that it takes 3 seconds to load one cubic foot of cargo, and 20 seconds to board a passenger. The time it takes to fly between the FLS and the CSG is the same random variable in both directions. For shorter flights, it is the triangular distribution with parameters (30, 65, 90) minutes, and for longer flights, the triangular distribution with parameters (100, 150, 200), as seen in Section 2.2. After the aircraft arrives at the CSG, the time required to unload cargo is 3 seconds for each cubic foot, and 20 seconds for each passenger—the same as the loading time. In addition, the aircraft may need to refuel, go through standard procedures for safety checks and paperworks, and perhaps load cargo and passengers (heading for the FLS), before it can take off for the return trip. This random time is modeled by a triangular distribution with parameters (20, 45, 100) minutes, consistent with the observations in Section 2.3.

Each aircraft is assumed to be available 75% of the time in the long run, so the RFT (ready for tasking) at the FLS is  $0.75 \times 2 = 1.5$ . To model failure and maintenance, we will use an exponential distribution for the time between failures, with a mean of 15 days. The time

to repair is modeled by a triangular distribution with parameters (2, 5, 8) days, to model the parameters found in Chapter 2.

Currently, a typical schedule for the FLS is to reserve one day a week for maintenance, where no sorties are flown, and to fly two sorties every other day, while flying one sortie on the remaining days [2]. This results in 9 sorties per week, with a pattern of 1, 2, 1, 2, 1, 2, 0. However, at times tasking comes in waves and requirements can change. In our model, we enforce a rule such that there are at most 2 sorties within any 24-hour window. In other words, in each week the FLS can support up to 14 sorties if need be, but the number can fluctuate if the demand does not call for it. The reason that we adopt this assumption is that there is no data for how the sorties will be scheduled when the FLS moves to adopt three V-22 aircraft in the future, so we want to make assumptions that can be applied to both aircraft types in order to compare them.

### 3.3.2 V-22 Osprey

Another aircraft that is of interest in this study is V-22 Osprey, since the Navy has decided to switch to V-22 Osprey to support the COD in the near future [6], [7]. The V-22 variant for the COD mission is designated as CMV-22B [7]. Based on studies of the V-22, four different configurations of the V-22 can be used for COD operations [13], which are summarized in Table 3.2. The triwall is a large cardboard box that can hold cargo and contributes to the total amount of volume the airplane can carry. Each passenger has an equivalent volume of 15.5 cubic feet for the V-22, and the table shows the equivalent cubic feet for each configuration. Again, since each passenger brings personal luggage of 7.5 cubic feet, the available cargo space is reduced by the same amount. For instance, with the first configuration, the available cargo space is

$$128 - 17 \times 7.5 = 0.5.$$

In other words, the first configuration essentially cannot take any additional cargo when 17 passengers go onboard.

We assume the same long-run availability of 75% for each V-22 as that for the C-2. The RFT is therefore  $0.75 \times 3 = 2.25$ , since the FLS has three V-22. The failure and maintenance cycles, the flight times, and the loading times are assumed to be the same for both C-2 Greyhound aircraft and V-22 Osprey aircraft.

Table 3.2. Feasible V-22 cargo space configurations.

Configuration	Cargo (cubic feet)	Passengers	Equivalent
83 Box + Triwall	128	17	391.5
166 Box + Triwall	211	11	381.5
249 Box + Triwall	294	7	402.5
332 Box + Triwall	377	1	392.5

Since there are three V-22 aircraft, we enforce a rule such that at most 3 sorties can be scheduled within any 24-hour window. In other words, in each week the FLS can support up to 21 sorties if need be, but the number can fluctuate if the demand does not call for it. This rule allows us to better compare the cargo delay between the C-2 Greyhound and V-22 Osprey.

### 3.4 Sortie Policies

In our model, when an aircraft returns to the FLS from the CSG, the FLS will either schedule a sortie immediately, or delay. There are three sources of delay: (1) the plane requires repair; (2) the time elapsed since the second-to-last C-2 sortie (or the third-to-last V-22 sortie) is less than 24 hours; (3) there is not enough inventory at the FLS to justify a flight. The next sortie will be scheduled as soon as these reasons for delay have expired.

The first column in Figure 3.2 depicts this activity at the FLS. Once a plane has landed at the FLS, it will undergo repair, if needed. The FLS will then enforce a policy of limiting the number of sorties in the past 24 hours (two for the C-2 and three for the V-22). This is enforced by demanding planes have a permission slip before proceeding to the loading phase of the process. In any 24-hour period, the number of permission slips given out cannot exceed a quota (two for the C-2 and three for the V-22). A working plane will either be given a permission slip immediately, if the quota has not been exceeded, or a delayed permission slip, granting permission to proceed at the earliest possible time.

Once a plane can proceed to the loading phase of the process, two decisions must be made. First, we need to decide which configuration will be used, as shown in Tables 3.1 and 3.2. Second, we need to examine whether there is enough cargo and passengers at the FLS to

justify a sortie. In order to make these decisions, we need to convert each passenger to an equivalent cubic feet so that we can compare cargo and passengers with the same unit. For C-2, each passenger is equivalent to

$$\frac{415 - 103}{26 - 2} = 13$$

cubic feet, as shown in Table 3.1. For V-22, each passenger is equivalent to

$$\frac{377 - 128}{17 - 1} = 15.5$$

15.5 cubic feet, as shown in Table 3.2.

A load is deemed *valid* if the equivalent cubic feet exceeds 90% of the aircraft's full capacity; otherwise, it is deemed *invalid*. Not all configurations of a plane have the same maximum volume. We take 90% of the smallest configuration. For the V-22, this is 90% of 381.5 ft<sup>3</sup>, as found in Table 3.2. If the loading is *valid*, the airplane will fly to the CSG. If all load configurations are invalid, the plane will wait until there is more cargo or passengers at the FLS and go through the same evaluation again. Each valid configuration will get scored, and the valid configuration with the highest score will be used. Figure 3.3 depicts this process.

We next explain the score of a load in detail in Section 3.4.1, and then introduce a priority-based loading policy in Section 3.4.2.

### 3.4.1 Score of a Load

The score of a load is a real valued function of the set of items loaded onto a plane. If there are several valid configurations, then we choose the configuration with the highest score, and configure and load the aircraft accordingly. If none of the configurations are valid, then we wait for the next opportunity to schedule a sortie. Scoring requires assigning a numerical values to each priority level, called *weights*. We develop our scoring scheme here, and explore two different scoring *weights* via a numerical experiment in Section 4.1.

Given  $n$  priority levels, a priority weight is a set of  $n + 1$  numbers. Each priority level is assigned a weight, and the last weight represents the weight of a high priority item that has



been waiting at the FLS for a very long time. The most important priority level is denoted  $i = 1$ , and the less important priority levels are larger integers. The extra weighting number corresponds to  $i = 0$ , and its use will soon be apparent.

If  $A$  is the set of items that are loaded onto a plane in a given configuration, its score is

$$s(A) = \sum_{a \in A} V_a \cdot \left[ w_{i_a} + (w_{(i_a-1)} - w_{i_a}) (1 - e^{-\lambda \Delta t_a}) \right], \quad (3.2)$$

where  $i_a$ ,  $V_a$ , and  $\Delta t_a$  are the priority, volume, and wait time, for item  $a$ . If item  $a$  is a person, then person's equivalent volume is used for the term  $V_a$ , which is 13 cubic feet for C-2 and 15.5 cubic feet for V-22. The score of a load is the sum of scores for each individual item. Adding an additional item increases the score by an amount that is a function of that item's characteristics only, and not what is already on the plane. There is no bonus for shipping certain items together in a 'bundle' or penalty for shipping incompatible cargo together.

For an individual item, the score is proportional to its volume. As seen in Equation (3.2), a newly-arrived item with priority  $j$  will initially have a weight  $w_j$ , and this weight increases over time, and approaches  $w_{j-1}$ , as the weight time approaches infinity, for  $j = 1, 2, 3, 4$ . Our score places greater importance to the priority level than to the waiting time. A low priority item, even after waiting for a very long time, will never exceed the score of another item with a higher priority of the same size.

We take  $\lambda = \ln(2)/T_0$ , with  $T_0 = 24$  hours. The parameter  $T_0$  acts as a half life, the individual scores 'decay' upward to the maximal score.

### 3.4.2 A Priority-Based Policy

Items at the FLS are sorted first by their priorities, and then by their waiting times at the FLS. For a given cargo space configuration, items (an engine, a group of passengers, or cargo) are loaded into the proposed configuration according to this sorted list as long as they can fit, until no more items can be loaded.

Since all engines share the same priority 1, if there are two or more engines waiting at the FLS, the one that has been waiting the longest will be loaded. Although all distinguished

visitors will be considered for boarding before the regular passengers, it is not guaranteed that all distinguished visitors will board before any of the regular passengers. For instance, if there are 2 seats left, a group of 3 distinguished visitors will not be able to board, but a group of 2 regular passengers will.

Cargo is treated as a continuous variable. With real-time cargo tracking, all cargo with priority 1 will be loaded to the aircraft, before any cargo with priority 2, followed by priorities 3, then 4. Within the same priority, cargo that has been waiting at the FLS for the longest will be loaded first, and then the second longest, and so on. In other words, cargo is sorted by priority category, with ties being broken by the amount of time spent waiting at the FLS. Without real-time cargo tracking, we assume that cargo is treated in the first-come-first-served manner, and has a lower priority than engines and passengers. Hence, we set the priority of all cargo to 3, so that all cargo will be loaded to the airplane entirely based on their arrival times.

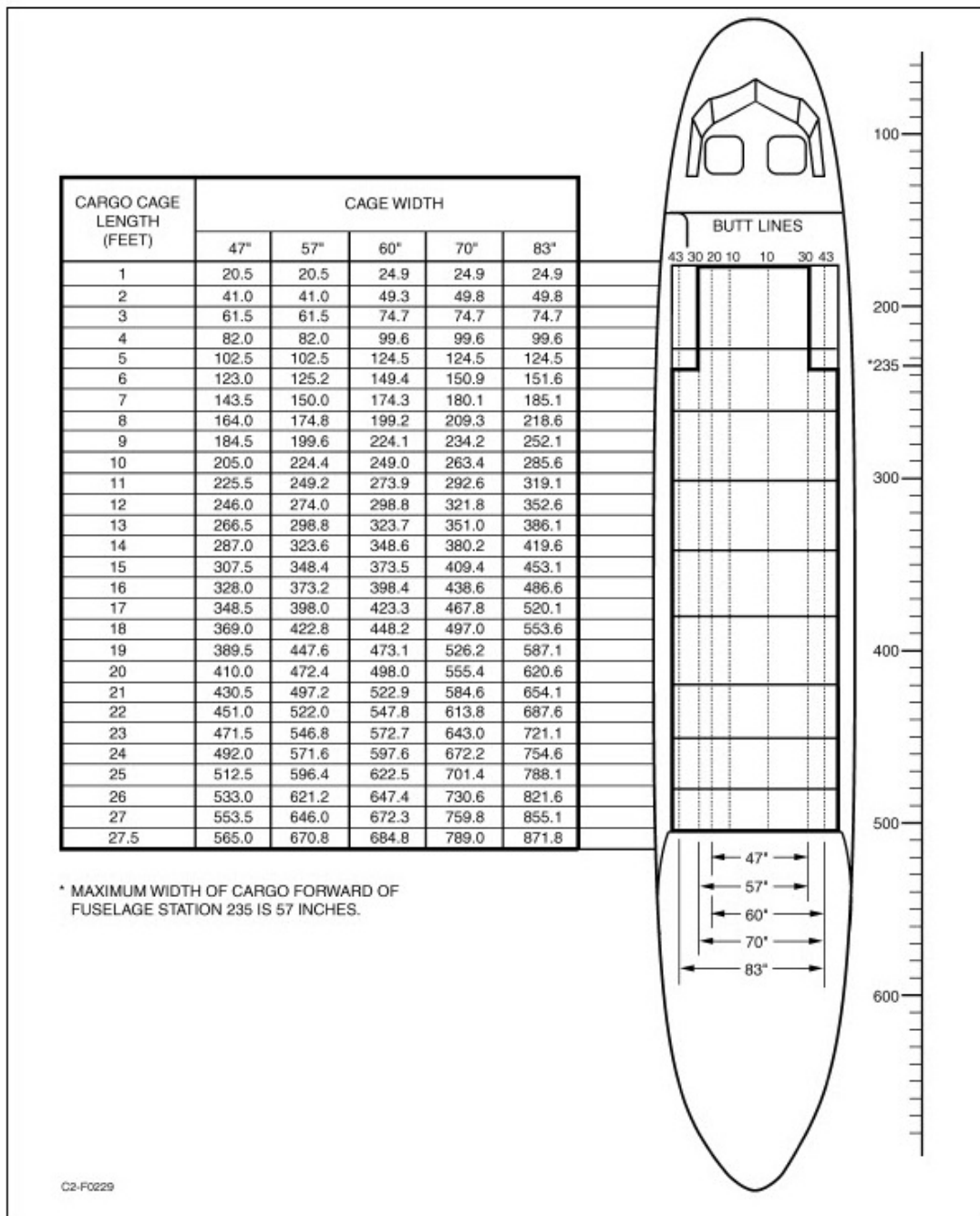


Figure 3.1. C-2 Greyhound has nine sections. The forward sections are configured to carry cargo and the aft sections to carry crew and passengers [2]

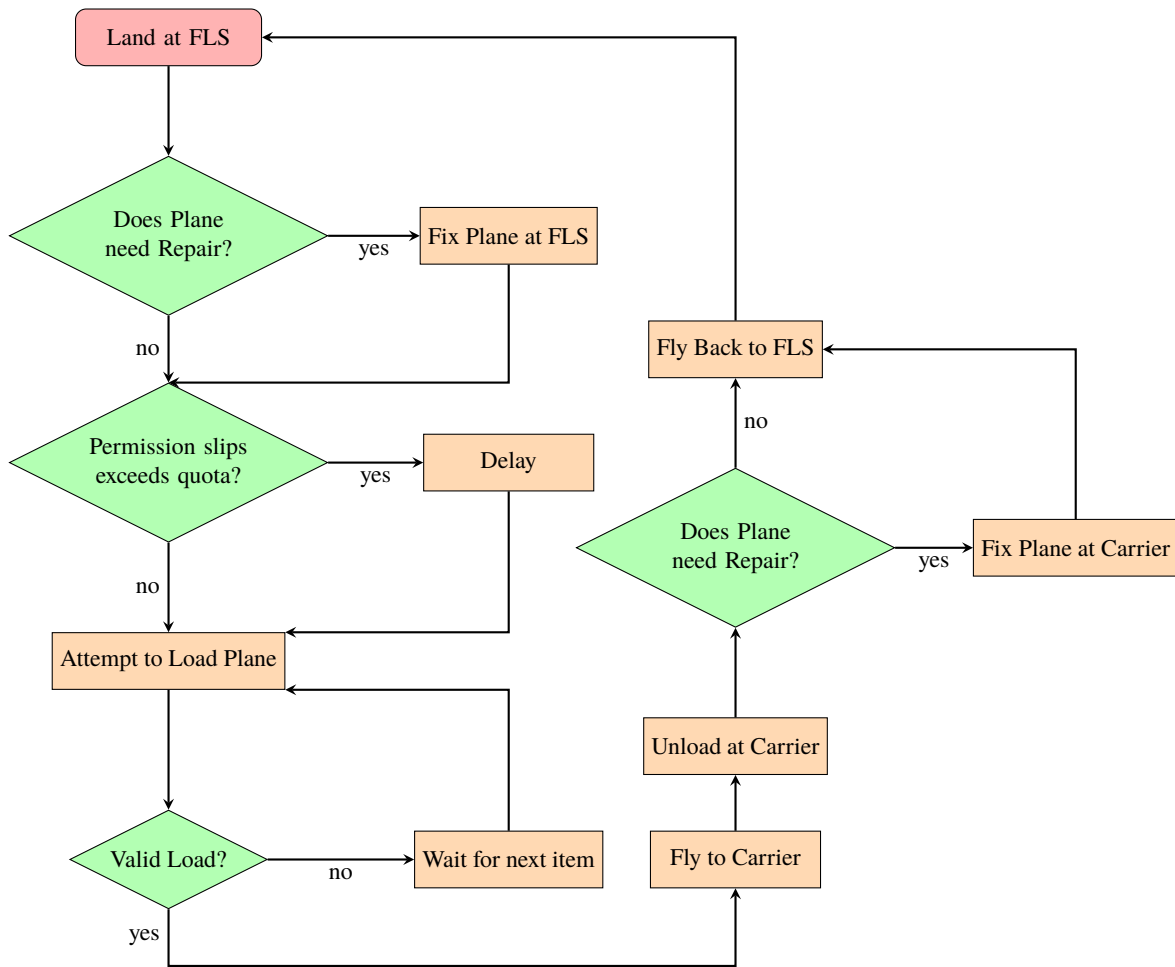


Figure 3.2. The operational cycle of an aircraft.

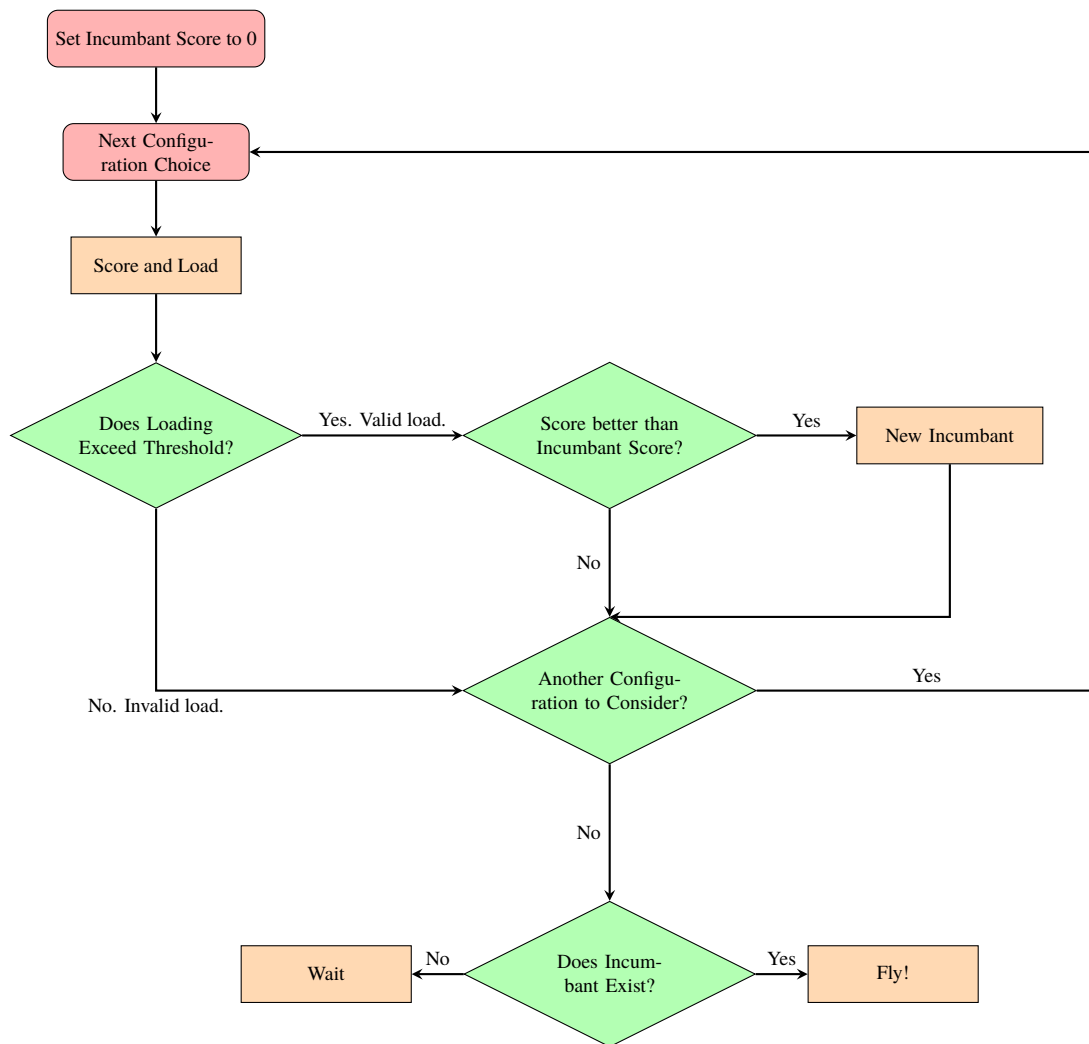


Figure 3.3. A procedure to determine which cargo space configuration to use for the next sortie.

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## CHAPTER 4:

# Simulation Results and Analysis

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This chapter presents several numerical experiments based on the simulation model described in Chapter 3. The simulation model is implemented in Python using the `SimPy` and `NumPy` packages [20]–[22]. The main purpose of the simulation experiments is to gain insights into how a cargo tracking system can reduce the delay of high-priority cargo, and how the delay might depend on the aircraft platforms C-2A and CMV-22B.

Our main purpose is to compare cargo tracking capabilities, mission scenarios, and aircraft configurations. Hence, in the simulation experiments, we control two environmental sources of randomness in order to reduce the variance of the difference in delay among these simulation runs. First, we generate an arrival process for cargo, passengers, and engines at the FLS to be transported to the CSG, and use this same arrival process for all simulation experiments. Second, we generate several aircraft breakdown profiles—a sequence of up times and down times for an aircraft—and use the same breakdown profiles for aircraft in different simulation experiments. By controlling these two sources of randomness, we can reduce the probability that the difference in simulation results are due to luck rather than due to the factors we are interested in studying.

For each operational scenario, we run the simulation for 100 weeks, and collect the delay data for items that arrive in the middle 90 weeks. We use the first 5 weeks to warm up the simulation, and then we use the last 5 weeks to ensure that all items arrive during the middle 90 weeks will ship to the CSG so as to collect those delay data.

### 4.1 Linear Scores and Exponential Scores

A higher priority item will receive a higher score than a lower priority item. In the first simulation experiment, we explore two scoring schemes: linear scoring scheme and exponential scoring scheme. Table 4.1 summarizes the priority weights of these two scoring schemes. As a normalization, the priority weight given to the lowest priority level—namely, level 4—is taken to be one. In the linear scoring scheme, the score increases by a unit step for each increase in priority level; in the exponential scheme, the score doubles for each

increase in priority level. Recall from Section 3.4.1 that an item with priority level 1 will initially have a priority weight  $w_1$ , and increases over time and approaches  $w_0$  as its waiting time approaches infinity.

Table 4.1. Priority weights of two scoring schemes.

	Priority Level				
	0	1	2	3	4
Linear Scoring Scheme	5	4	3	2	1
Exponential Scoring Scheme	16	8	4	2	1

In all of our numerical experiments, we compare an FLS that has real-time cargo tracking capabilities to an FLS that does not have real-time cargo tracking capabilities. An FLS can always identify an engine and a group of distinguished visitors, regardless of its ability to track cargo priorities. Since an FLS without real-time cargo tracking capabilities cannot distinguish different priorities of continuous (non-engine) cargo, we set all cargo to priority 3 to account for this inability. Table 4.2 summarizes the priority levels between these two scenarios.

Table 4.3 reports the average delay of engines, cargo, and passengers, when the linear scoring scheme is used. We first generate three aircraft breakdown profiles, where each profile consists a sequence of up time and down time for one aircraft, over the period of 100 weeks. Since there are only two C-2 planes, in each simulation run, we need only two aircraft breakdown profiles. For each subset of two breakdown profiles, we repeat the simulation 8 times, hence a total of 24 simulation runs. The left-hand side right side of Table 4.3 reports the results of 24 simulation runs of an FLS that does not have real-time cargo tracking capability, while the right-hand side reports the results of 24 simulation runs

Table 4.2. Priority levels for the case with cargo tracking and the case without cargo tracking.

	Cargo Tracking	No Cargo Tracking
Engine	1	1
Passengers	1,2	1,2
Cargo	1,2,3,4	3



of an FLS that implements a real-time cargo tracking. Since an FLS that lacks the ability to track cargo cannot distinguish cargo priorities, the left part of Table 4.3 is partially blank.

Table 4.3. Numerical experiments with C-2 using the linear scoring scheme.  
Delivery times are given in hours.

	No Cargo Tracking (Average:10.65 flights per week)					Cargo Tracking (Average:10.67 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	6.8	0.29	2.3	4.8	15.4	6.5	0.25	2.3	4.8	14.7
All Passengers	17.2	0.26	12.9	20.8	31.9	16.9	0.24	12.7	20.6	31.9
VIP	14.8	0.20	11.1	18.5	27.0	14.5	0.21	11.0	18.6	27.1
Non-VIP	17.7	0.27	13.2	21.3	32.9	17.3	0.25	13.0	21.0	32.9
All Cargo	30.8	1.47	14.6	27.9	89.4	32.1	1.67	13.7	25.2	85.7
Priority 1						14.3	0.15	10.6	17.9	26.2
Priority 2						15.4	0.20	10.8	18.4	28.6
Priority 3						19.3	0.44	11.3	19.5	37.0
Priority 4						39.9	2.41	15.5	31.8	120.2

As seen in Table 4.3, among the common metrics shared by ‘no cargo tracking’ and ‘cargo tracking’, there is little change in the delay times. However, the ability to track cargo priorities substantially shortens the delay for cargo with priority levels 1, 2, 3, while lengthening the delay only for the lowest priority cargo. The average delay for cargo in priority levels 1 and 2 reduce by more than 50%, to become comparable to the delay for passengers. The average delay for the cargo of priority level 4 increases about 25%. The cargo of priority level 4 also experiences the largest variance in the delay time, since its delay may be up to several days if there is a long queue at the FLS, or if one or both aircraft are down when the cargo arrives.

Table 4.4 summarizes the simulation results where we apply the exponential scoring scheme to a load, as discussed in Table 4.1. Analogous to the case of linear scoring scheme, 24 simulation runs are dedicated to the case of ‘no cargo tracking’ while another 24 simulation runs are dedicated to the case of ‘cargo tracking’. With cargo tracking, the delays for engines and passengers stay roughly the same; the cargo in priority levels 1, 2, 3 all have a smaller delay, while the cargo in priority level 4 has a longer delay.

As seen in Tables 4.3 and 4.4, the performance measures are very similar between the linear scoring scheme and the exponential scoring scheme. The small differences can

Table 4.4. Numerical experiments with C-2 using the exponential scoring scheme. Delivery times are given in hours.

	No Cargo Tracking					Cargo Tracking				
	(Average:10.67 flights per week)					(Average:10.67 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	6.6	0.26	2.3	4.8	14.6	6.7	0.26	2.3	5.0	15.0
All Passengers	16.8	0.21	12.7	20.6	31.0	17.1	0.25	12.6	20.5	32.2
VIP	14.6	0.16	10.9	18.5	26.6	14.6	0.20	11.0	18.3	26.8
Non-VIP	17.3	0.22	13.0	21.0	31.8	17.6	0.27	12.9	21.0	33.1
All Cargo	31.5	1.39	14.5	28.2	90.0	32.2	1.61	13.9	25.5	87.6
Priority 1						14.4	0.15	10.6	17.8	26.0
Priority 2						15.7	0.23	10.9	18.4	29.1
Priority 3						20.0	0.38	11.4	19.6	39.0
Priority 4						39.9	2.33	15.7	34.1	121.4

be attributed to statistical fluctuation of the simulation, and the simulation results do not support any justification whether one scoring scheme is stronger than the other. In the rest of this chapter, we use the linear scoring scheme to conduct the other simulation experiments.

## 4.2 Longer Range with Reduced Payload for C-2A

In our model, we measure the cargo in terms of its volume rather than its weight, since in most cases, the volume is the single limiting factor. A typical cargo density is 3–5 pounds per cubic feet. If we fill either C-2 or V-22 with cargo of this density, then a full load of cargo does not come close to reach the maximal payload, as seen in Table 1.1. There are, however, situations where the payload becomes the limiting factor. For example, a C-2 aircraft’s payload drops when it needs to travel a longer range, or when the temperature increases in summer time. This section presents simulation experiments to explore this situation.

We consider a scenario where the carrier sits at a longer distance from the FLS. We use the larger mode in Figure 2.3 to model the flight time, which follows a triangular distribution with parameters (100, 150, 200)—instead of (30, 65, 90), which is previously used in Section 4.1. In order to use our simulation model, we assume that the *allowable* cargo volume is now only a ratio  $r \leq 1$  of the aircraft’s cargo space. For instance, if  $r = 0.9$  and we use the configuration with 4 rows of seats and 5 sections of cargo, as seen in

Table 3.1, then we can board 14 passengers, but can load cargo only up to  $259 \times 0.9 = 233.1$  cubic feet. For the purpose of determining whether a load is valid and computing the score of a load, the contribution from loaded cargo is scaled back by multiplying with  $1/r$ , so that the equivalent cubic feet is again 441 for all configurations. These reductions do not affect the plane's ability to fly an engine, and nothing else, to the carrier.

We set  $r = 1$ ,  $r = 0.9$ , and  $r = 0.8$ , and report the simulation results in Tables 4.5 to 4.7, respectively. Within each table, we can make similar observations to those in Table 4.3. In other words, with cargo tracking, the delays for engines and passenger remain roughly the same. The delays for cargo in priority levels 1, 2, 3 all decrease substantially, while the delay for cargo in priority level 4 increases.

Table 4.5. Numerical experiments with C-2, longer flight times, and full capacity. Delivery times are given in hours.

	No Cargo Tracking (Average:10.63 flights per week)					Cargo Tracking (Average:10.65 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	8.8	0.31	4.0	8.0	15.8	9.1	0.28	4.0	8.4	16.2
All Passengers	19.4	0.27	14.6	22.7	35.1	19.6	0.28	14.3	22.5	35.6
VIP	16.6	0.18	12.5	20.0	30.0	16.7	0.16	12.5	19.9	29.7
Non-VIP	19.9	0.29	15.0	23.1	36.2	20.1	0.31	14.6	22.9	36.9
All Cargo	36.7	1.91	16.9	32.4	108.9	39.1	1.91	15.9	29.5	113.5
Priority 1						16.5	0.21	12.1	19.2	28.4
Priority 2						18.0	0.27	12.4	19.9	32.3
Priority 3						23.1	0.53	13.0	21.5	47.6
Priority 4						49.1	2.75	18.3	41.3	154.2

Comparing across Tables 4.5 to 4.7, we see that as  $r$  decreases, the delay for engines and passengers increase slightly, while the delay of cargo increases substantially. With cargo tracking, the distribution of the delays (mean, and the 50th, 75th, and 90th percentiles) for cargo in priority levels 1 and 2 increase only slightly, while that for cargo in priority level 3 increases marginally. The distribution of the delay for cargo in priority level 4, however, increases substantially, including the mean, and the 50th, 75th, and 90th percentiles. It shows that real-time cargo tracking is particularly beneficial when the C-2 payload decreases if the CSG sits at a longer range, or if the temperature increases.

Table 4.6. Numerical experiments with C-2, longer flight times, and 90% cargo capacity. Delivery times are given in hours.

	No Cargo Tracking (Average:11.19 flights per week)					Cargo Tracking (Average:11.21 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	9.5	0.22	4.2	9.3	17.4	9.0	0.28	4.2	9.1	16.5
All Passengers	19.4	0.24	14.3	22.2	35.2	18.8	0.24	13.9	21.7	34.0
VIP	16.3	0.16	12.0	19.0	28.8	16.2	0.15	12.1	19.0	28.6
Non-VIP	20.0	0.26	14.7	22.7	36.5	19.2	0.27	14.3	22.1	35.1
All Cargo	45.9	1.44	18.2	46.6	139.6	45.6	1.87	16.0	33.5	132.0
Priority 1						15.8	0.17	11.5	18.4	26.9
Priority 2						17.6	0.23	11.9	19.3	32.0
Priority 3						22.8	0.46	12.6	20.8	46.0
Priority 4						59.2	2.73	19.3	56.9	180.1

Table 4.7. Numerical experiments with C-2, longer flight times, and 80% cargo capacity. Delivery times are given in hours.

	No Cargo Tracking (Average:11.90 flights per week)					Cargo Tracking (Average:11.93 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	10.8	0.29	5.7	11.0	18.5	11.1	0.31	6.0	11.6	18.7
All Passengers	19.9	0.32	14.5	22.4	35.6	19.8	0.29	13.9	21.7	36.4
VIP	16.1	0.20	11.7	18.3	28.1	16.1	0.16	11.8	18.5	28.2
Non-VIP	20.6	0.35	15.0	23.1	37.0	20.5	0.32	14.3	22.3	38.1
All Cargo	70.0	4.36	23.7	100.4	208.0	75.2	4.96	19.2	83.2	254.5
Priority 1						16.4	0.20	11.2	18.0	27.8
Priority 2						19.4	0.37	11.9	19.6	39.6
Priority 3						27.5	0.84	12.9	22.5	67.7
Priority 4						103.0	7.31	30.3	153.5	318.6

### 4.3 Different Capacities for CMV-22B

This section presents simulation results for FLS that stations three CMV-22B aircraft, which is designated by the Navy to replace C-2A Greyhound for COD mission in the near future. Unlike the C-2A, which has been supporting the COD mission for decades, there is no data on actual CMV-22B COD sorties. Patuxent River conducted a cargo study for CMV-22B [13], and there is still ongoing study to determine the exact configurations, payload, and cargo capacity [14]. In our simulation experiments, we set the cargo capacity according to the cargo study [13], and explore the cases if the cargo space is reduced to 90%, 80%,

and 70%, of that in the cargo study.

In order to compare C-2A and CMV-22B, we use the same arrival process for cargo, passengers, and engines at the FLS, as well as the same aircraft breakdown profiles. Recall that in Section 4.1, we generate three aircraft breakdown profiles, and let the two C-2A use two of the three in a simulation run. Since the FLS will station three CMV-22B, we just use all three breakdown profiles—one for each CMV-22B—in each simulation run. In each scenario, we repeat the simulation for 24 independent simulation runs. Each simulation run lasts for 100 weeks, and we collect the delay data for items arriving in the middle 90 weeks to estimate their delays.

We set  $r = 1, 0.9, 0.8$ , and  $0.7$ , and report the simulation results in Tables 4.8 to 4.11, respectively. Within each table, we can make similar observations to those in Table 4.3. In other words, with cargo tracking, the delays for engines and passenger remain roughly the same. The delays for cargo in priority levels 1, 2, 3 all decrease, while the delay for cargo in priority level 4 increases. Since now we have three CMV-22B, and we allow up to three sorties in each 24-hour window, the FLS can deliver items much faster. A long delay may still happen when all three aircraft break down, but it is much more unlikely. As a consequence, there is not a large difference between delays for cargo in priority levels 1, 2, 3, while the delay of cargo in priority level 4 does not fall far behind, except when  $r$  drops to  $0.8$  and  $0.7$ .

Table 4.8. Numerical experiments with V-22, full cargo capacity.  
Delivery times are given in hours.

	No Cargo Tracking (Average:12.48 flights per week)					Cargo Tracking (Average:12.49 flights per week)				
	mean    std err		Percentile			mean    std err		Percentile		
			50	75	90			50	75	90
Engines	2.7	0.07	2.2	2.4	2.5	2.8	0.08	2.2	2.4	2.6
All Passengers	11.3	0.08	9.4	15.5	22.0	11.3	0.08	9.4	15.5	22.1
VIP	10.2	0.09	8.3	13.9	19.5	10.2	0.10	8.5	14.0	19.8
Non-VIP	11.5	0.08	9.6	15.8	22.4	11.5	0.07	9.6	15.7	22.5
All Cargo	12.3	0.18	9.5	15.8	23.0	12.3	0.17	9.3	15.6	23.0
Priority 1						10.1	0.07	8.2	13.8	19.7
Priority 2						10.2	0.07	8.2	13.9	19.9
Priority 3						10.6	0.11	8.3	13.9	20.1
Priority 4						13.3	0.21	10.0	16.6	24.7

Table 4.9. Numerical experiments with V-22, 90% cargo capacity.  
Delivery times are given in hours.

	No Cargo Tracking (Average:13.18 flights per week)					Cargo Tracking (Average:13.18 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	2.8	0.05	2.2	2.4	2.6	2.8	0.05	2.2	2.4	2.6
All Passengers	10.8	0.08	8.8	14.7	21.5	10.9	0.06	8.8	14.8	21.6
VIP	9.7	0.07	7.9	13.7	18.9	9.9	0.06	7.8	13.7	19.1
Non-VIP	11.0	0.08	9.0	14.9	21.9	11.1	0.06	9.0	15.1	22.0
All Cargo	11.8	0.18	9.0	14.9	22.0	12.4	0.15	8.9	15.0	22.3
Priority 1						9.2	0.04	7.4	12.7	18.2
Priority 2						9.4	0.04	7.5	12.8	18.5
Priority 3						10.0	0.07	7.6	13.0	19.0
Priority 4						13.9	0.21	9.7	16.2	24.5

Table 4.10. Numerical experiments with V-22, 80% cargo capacity.  
Delivery times are given in hours.

	No Cargo Tracking (Average:14.02 flights per week)					Cargo Tracking (Average:14.03 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	2.9	0.07	2.2	2.4	2.7	2.9	0.07	2.2	2.4	2.6
All Passengers	11.3	0.09	9.1	15.1	22.0	11.1	0.08	9.0	14.9	21.7
VIP	9.3	0.06	8.0	12.4	17.8	9.3	0.07	7.9	12.6	17.9
Non-VIP	11.6	0.10	9.4	15.7	22.5	11.4	0.09	9.3	15.5	22.1
All Cargo	11.3	0.18	8.0	14.0	20.8	11.4	0.20	7.9	13.9	20.5
Priority 1						8.3	0.05	6.6	11.6	16.8
Priority 2						8.4	0.05	6.6	11.7	16.8
Priority 3						8.8	0.09	6.7	11.9	17.3
Priority 4						12.9	0.28	8.7	15.1	22.7

Comparing across Tables 4.8 to 4.11, somewhat surprisingly, some categories of performance improve as  $r$  decreases. For instance, the average delay for passengers with  $r = 0.9$  is 10.9 hours, while that with  $r = 1$  is 11.3 hours. The reason is that with  $r = 0.9$ , the aircraft's cargo space *fills up* sooner, so a sortie will be dispatched sooner, and as a consequence, more frequently. As seen in Tables 4.8 and 4.9, the average number of sorties with  $r = 1$  is 12.49 per week, while that with  $r = 0.9$  is 13.18 per week. In other words, the shorter delay comes at the cost of more frequent sorties.

Table 4.11. Numerical experiments with V-22, 70% cargo capacity.  
Delivery times are given in hours.

	No Cargo Tracking (Average:15.13 flights per week)					Cargo Tracking (Average:15.15 flights per week)				
	mean	std err	Percentile			mean	std err	Percentile		
			50	75	90			50	75	90
Engines	3.0	0.05	2.2	2.4	2.9	3.1	0.04	2.2	2.4	3.1
All Passengers	10.3	0.07	8.0	13.9	20.7	10.3	0.08	8.0	13.8	20.6
VIP	8.7	0.09	6.9	11.8	17.3	8.9	0.08	7.0	11.9	17.5
Non-VIP	10.6	0.07	8.3	14.3	21.2	10.6	0.08	8.2	14.1	21.2
All Cargo	11.4	0.17	7.5	13.1	21.3	12.0	0.21	7.4	13.1	21.2
Priority 1						7.7	0.06	5.8	10.5	15.7
Priority 2						7.8	0.06	5.9	10.5	15.7
Priority 3						8.4	0.11	6.0	10.8	16.4
Priority 4						14.0	0.29	8.4	14.9	24.3

We can also compare the performance of the CMV-22B in Tables 4.8 to 4.11 with those for the C-2A in Table 4.3. A set of three CMV-22B Ospreys outperform a set of two C-2A Greyhounds by a substantial margin. The main reason is that the capacity of CMV-22B is only slightly smaller than that of C-2A, so having one more aircraft results in a significant advantage. In addition, we allow up to three CMV-22B sorties in each 24-hour window, which helps alleviate the impact when there is a surge of arriving engines, passengers, or cargo. Having only two C-2A aircraft, the fraction of time that both C-2A aircraft are down is  $0.25^2 = 0.0625$  or 6.25%, and when it happens, items may need to wait for a prolonged period of time before getting delivered. With three CMV-22B aircraft, the fraction of time that all three CMV-22B aircraft are down is only  $0.25^3 \approx 0.0156$  or 1.56%, which is much smaller than that with two C-2A aircraft.

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## CHAPTER 5:

### Conclusion

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This thesis studies how real-time cargo tracking can improve the delivery times of high priority cargo items in the carrier onboard delivery (COD) mission. We analyze data provided by VRC-30, develop a simulation model, and run simulation experiments to compare several scenarios. Our simulation model can be run with a variety of model parameters, including the arrival process of cargo, passengers, and engines at the forward logistics site (FLS), the flight time of the aircraft, the aircraft's capacity, the aircraft's breakdown and repair cycles, and many others.

#### **5.1 Key Results**

Currently the Navy uses C-2A to support the COD mission, and typically stations an FLS with two C-2A aircraft. By inferring model parameters from data obtained from VRC-30, our simulation results indicate that the real-time cargo tracking can reduce the delay of high-priority cargo by more than 50%, while increasing the delay of low-priority cargo by about 25%. In the coming years, the Navy plans to replace C-2A with CMV-22B for the COD mission, and will station each FLS with three CMV-22B. By using a cargo study report [13], our simulation results indicate that the real-time cargo tracking can reduce the delay of high-priority cargo by 17–35%, while increasing the delay of low-priority cargo by 8–17%.

#### **5.2 Assumptions and Limitations**

Because the data provided by VRC-30 do not include some specifics on the COD sorties, we need to make a few assumptions and educated guesses. For instance, the data does not indicate when large replacement parts, such as F-18 engines, are delivered, and does not record whether a delay of a C-2A on the carrier is due to breakdown and repair, or other reasons. The data also does not record the time points when passengers and cargo arrive at the FLS, so that we have to make a few assumptions to develop the model for how cargo and passengers arrive at the FLS.

There is no data on COD mission performed by CMV-22B. As such, our model parameters on CMV-22B are based on ongoing studies on its cargo capacity. We also assume that the probabilistic nature of CMV-22B's breakdown and repair cycles is identical to those of C-2A. Whereas there will typically be three CMV-22B aircraft stationed at a FLS, those CMV-22B may need to support other types of mission. Since we do not have that information, in our simulation experiments, we assume that all three CMV-22B aircraft are dedicated to the COD mission. As a consequence, the delivery time with three CMV-22B is much shorter than that with two C-2A, since the cargo capacity of CMV-22B is only marginally smaller than that of the C-2A.

### **5.3 Future Work**

As the cargo study of CMV-22B becomes more mature, it is worthwhile to run our simulation models with updated parameters to better inform the delivery times of various items. If there are additional data to help infer model parameters, then it is possible to produce simulation results to better inform decision-makers.

We use a priority-based policy to model how one can do with the real-time cargo tracking capability. The priority-based policy sorts the items first by priority and then by their arrival times, and load the items accordingly. In the case of no cargo tracking, we load items based on their arrival times—analogous to a first-come-first-served policy. The current practice can be a mixture between the two—load high priority cargo first most of the time but not always. Another benchmark that would be interesting to include in the study is the case where all the cargo are loaded at random. While the average cargo delay will stay roughly the same, such a practice will cause a very long tail in the delay distribution—some cargo will experience a very long delay before getting delivered to the carrier.

In our model, the breakdown and repair times for all aircraft are independent of each other. In practice, when one aircraft breaks down, its working parts can be used to repair the other aircraft of the same type. Therefore, when one aircraft breaks down, it becomes less likely for the other aircraft of the same type to break down during the same period of time. Accounting for this practice requires additional model development and new simulation codes.

Our simulation experiment assumes the same arrival rates of cargo, engines, and passengers,

over 100 weeks, in order to obtain delay statistics in steady state. In practice, the demand may surge temporarily, or go through cycles for various reasons. When there is surge of demand, it is an important measure how the FLS can adapt to a different policy in order to manage the delivery time of high-priority cargo. While it is possible to use our current simulation model to evaluate some of these scenarios, it is a major task to develop these scenarios carefully.

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## APPENDIX A:

### Technical Appendix

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The `Python` code used to implement the model presented in Chapter 3 is compatible with versions 3.5 and 2.7 of `Python` and available upon request. It uses the simulation library `SimPy` version 3. Please note that the syntax of `SimPy` version 3 is drastically different from version 2, and not compatible.

Simulations were run on desktop computers with Intel i7 processors. Each run that simulates 100 week's worth of items arriving to and FLS takes several minutes to complete. Simulations involving three planes (V-22) will take longer than simulations with only two planes (C-2). Also, if the rate at which items can be removed from the FLS is smaller than the rate at which they arrive, an object called the *M2* matrix will get arbitrarily large and cause the simulation time to be very long.

The `simpy` package is a process-based discrete-event simulation framework. The unit of time is one minute. These are converted to hours in the analysis stage. The simulation is broken into three different scripts, two preliminary scripts, and the main script. The first preliminary script generates the arrivals to the FLS and the second script generates the breakdown and repair times of the planes. These are written to files and fed to the main script, which simulates the delivery of the items from the FLS to the carrier. All three scripts could be run together in perpetuity, but we separate these processes to control for randomness and to model cargo-tracking and a lack of cargo-tracking as described in Chapter 4.

The sorting algorithm described in Section 3.4 uses the `NumPy` lexicographical sort. Moreover, to boost the speed of the simulation, we define a dynamic array class, which can change the size of a array quickly. It replaces the standard `append` algorithm in `numpy`, which is very slow, and it gives the sorting algorithms fewer items to sort.

Three arrays are kept in memory during simulation, *M1*, *M2*, and *M3*. *M1* is a `NumPy` structured array and contains information of all items that will eventually arrive at the FLS. *M2* and *M3* are dynamic array classes. *M1* is loaded from a file, and *M1* never changes

during the simulation. *M2* represents items currently waiting at the FLS. Items listed in *M1* are copied to *M2* as needed. As items are loaded into planes and fly, they are removed from *M2* and moved to *M3*. As planes arrive to the carrier, they are marked as ‘delivered’ on *M3*. Cargo items are modeled as a continuous variable. If the volume of cargo at the FLS is greater than the remaining cargo plane on the plane, the cargo is split. The plane is filled to it’s capacity, and the remaining stays at the FLS. Figure A.1 shows a self loop from *M2* to itself, to indicate events when continuous cargo is split, and some is placed on a plane (*M3*), and the remainder stays at the FLS (*M2*).

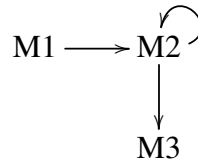


Figure A.1. The logical flow of three dynamic arrays.

The sorting process described in Section 3.4.2 only needs to act on *M2*, which greatly improves performance.

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## Initial Distribution List

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1. Defense Technical Information Center  
Ft. Belvoir, Virginia
2. Dudley Knox Library  
Naval Postgraduate School  
Monterey, California